

Enhanced Defect Detection in Additive Manufacturing Through In-Situ Vibration and Acoustic Data Fusion

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Abstract:

Additive manufacturing (AM) is transforming modern production methods by enabling the fabrication of complex structures with high precision and customization. However, the layer-by-layer construction inherent in AM introduces unique challenges, particularly the risk of internal defects that compromise structural integrity. Conventional post-processing inspection techniques are often inadequate for real-time defect detection, necessitating the development of effective in-situ monitoring solutions. This paper proposes an innovative approach combining vibration and acoustic emission data collected during fabrication to detect defects in real-time. Using advanced signal processing and data fusion techniques, we analyze how the synergy between these two modalities can enhance the sensitivity and accuracy of defect detection. The proposed method is validated through experimental trials on metal additive manufacturing systems, demonstrating superior performance over single-sensor monitoring strategies. The findings highlight the significant potential of multi-modal sensor fusion for ensuring the reliability and safety of additively manufactured components.

Keywords: Additive Manufacturing, Defect Detection, In-Situ Monitoring, Vibration Analysis, Acoustic Emission, Data Fusion, Signal Processing

I. Introduction

Additive manufacturing (AM) has gained remarkable traction across industries such as aerospace, automotive, and biomedical engineering [1]. Its ability to fabricate complex

geometries with reduced material wastage and design flexibility offers distinct advantages over traditional subtractive methods [2]. However, despite these benefits, the occurrence of defects such as porosity, delamination, and incomplete fusion remains a persistent problem. These defects, often introduced during the build process due to thermal gradients, powder inconsistencies, or mechanical issues, can severely impact the mechanical properties and reliability of the final parts. Addressing these challenges requires not only high-fidelity design but also robust quality assurance methodologies that can intervene during manufacturing. Traditional non-destructive evaluation (NDE) methods like ultrasonic testing, X-ray computed tomography, and optical inspections are usually performed post-production. While effective, they are reactive rather than proactive, often leading to high scrap rates, increased production costs, and potential undetected failures in critical components. Consequently, the AM community has shifted towards in-situ monitoring techniques aimed at detecting anomalies during the build process itself. Effective in-situ monitoring not only reduces the dependence on costly post-process inspections but also enables real-time corrective actions that can significantly enhance the quality and yield of AM parts [3].

In-situ monitoring approaches primarily focus on collecting thermal, optical, or mechanical signals generated during the printing process. Among these, mechanical signals—specifically vibrations and acoustic emissions—offer direct information about the dynamic state of the system and the material being processed. Vibrations can reveal anomalies in machine behavior or build integrity, while acoustic emissions can capture transient events like micro-cracking or layer delamination that are difficult to detect otherwise. Despite their individual potential, relying on a single type of signal can result in missed detections due to noise or limited sensitivity to certain defect types. The fusion of vibration and acoustic data presents a promising pathway to overcome these limitations. By combining these complementary modalities, it is possible to obtain a richer, more complete representation of the process conditions and defect signatures. Data fusion techniques can integrate information at multiple levels, from raw signal combination to high-level feature integration, enhancing the robustness and reliability of defect detection systems [4]. Yet, the optimal strategies for implementing such fusion in AM environments

remain an open research question, particularly given the harsh, noisy, and dynamic conditions typical of industrial printers.

In this paper, we investigate the integration of in-situ vibration and acoustic emission data for enhanced defect detection during metal additive manufacturing processes. Our approach employs both time-frequency analysis and machine learning-based fusion strategies to exploit the complementary nature of the two signal types [5]. Through extensive experimental validation, we demonstrate that multi-modal fusion significantly improves detection sensitivity, reduces false positives, and enables earlier identification of defects compared to single-sensor approaches. The results offer compelling evidence for adopting sensor fusion as a standard practice in next-generation AM quality assurance systems.

II. Methodology

The proposed methodology centers on the concurrent collection, processing, and integration of vibration and acoustic emission signals during the additive manufacturing process. To establish a reliable baseline, initial experiments were conducted using a Direct Energy Deposition (DED) system, a popular form of metal AM. High-fidelity piezoelectric accelerometers were strategically mounted on the print head and substrate to capture vibration signals across multiple axes. Simultaneously, wideband acoustic emission sensors were positioned in close proximity to the build platform to capture high-frequency stress waves indicative of material deformation and cracking events. Signal acquisition was performed at a high sampling rate (500 kHz) to preserve critical transient phenomena. Raw signals from both sensor types were preprocessed using a series of band-pass filters to eliminate irrelevant noise and machine-related background interference. The preprocessed signals were then subjected to feature extraction techniques such as Short-Time Fourier Transform (STFT) and Wavelet Transform to reveal their underlying time-frequency structures. This step was critical for identifying spectral patterns associated with different types of defects [6].

To facilitate effective data fusion, extracted features from both vibration and acoustic emission signals were aligned temporally and normalized to a common feature space. Early fusion

strategies, wherein features from both modalities are concatenated before classification, were employed alongside decision-level fusion methods, where each modality's outputs were combined through voting or weighted averaging schemes. Machine learning classifiers, including Support Vector Machines (SVM) and Random Forests, were trained on fused datasets to distinguish between normal and defective build conditions [7]. The models were validated using k-fold cross-validation to ensure robustness. In designing the experiments, specific defects were intentionally introduced into the build process to create a labeled dataset. These included controlled variations in laser power to induce lack of fusion, intentional disruptions in powder feed to simulate porosity, and deliberate mechanical vibrations to trigger layer misalignment. Each defect type was cataloged with corresponding sensor data, forming a comprehensive database for model training and evaluation. Ground truth validation was performed through post-process X-ray computed tomography, ensuring the accuracy of defect labeling [8].

Finally, performance metrics such as Precision, Recall, F1-score, and Receiver Operating Characteristic (ROC) curves were used to evaluate the effectiveness of the proposed multi-modal monitoring system. Comparative analyses were also conducted between single-sensor systems (vibration only, acoustic only) and the fused system to quantify the gains achieved through data fusion. The methodology was designed to be extensible to different AM processes, sensor configurations, and defect types, highlighting its broad applicability [9].

III. Experimental Setup

The experimental framework for validating the proposed defect detection system was established around a commercially available Direct Energy Deposition (DED) AM machine. A series of stainless steel 316L components were fabricated under controlled laboratory conditions. The print parameters were closely monitored and adjusted to introduce a range of manufacturing defects deliberately, such as porosity, incomplete fusion, and thermal cracking. The environmental variables like chamber temperature, shielding gas flow, and ambient noise levels were maintained constant across experiments to minimize extraneous influences on sensor readings. The vibration sensors selected were high-sensitivity piezoelectric accelerometers with a bandwidth of 0.5 Hz to 10 kHz, capable of capturing both low-frequency mechanical anomalies

and high-frequency resonances. For acoustic emissions, broadband sensors covering the 100 kHz to 1 MHz range were employed. Signal synchronization was achieved using a master-slave configuration of data acquisition systems, ensuring that vibration and acoustic data were temporally aligned to within microseconds.

Each fabrication run was divided into segments of approximately five minutes, during which specific anomalies were introduced according to a predefined schedule. During baseline runs, no anomalies were introduced, providing data representing defect-free manufacturing. All collected signals were time-stamped and annotated with corresponding build conditions, defect types, and system states. A total of 50 builds were conducted, resulting in a dataset containing over 200 hours of multi-modal sensor data. Signal processing pipelines were established for real-time feature extraction. For vibration signals, features such as Root Mean Square (RMS) amplitude, dominant frequency components, kurtosis, and spectral entropy were extracted. For acoustic signals, energy bursts, peak amplitude, event counts, and time-to-peak parameters were calculated. Principal Component Analysis (PCA) was used to reduce the feature space dimensionality while preserving the most discriminative information [10].

Machine learning models were trained offline using 70% of the dataset and tested on the remaining 30%. Hyperparameter tuning was performed using grid search strategies to optimize classifier performance. Specific attention was given to handling class imbalance resulting from the relatively lower number of defective segments compared to normal ones. Oversampling techniques such as SMOTE (Synthetic Minority Over-sampling Technique) were applied to balance the dataset before training. To validate the physical occurrence and location of defects, each manufactured part was subjected to X-ray computed tomography scanning at a resolution of 10 microns. Defect size, location, and type were documented and correlated with the time stamps of in-situ monitoring data. This cross-verification ensured that the ground truth for defect presence was accurate and reliable, providing a strong basis for evaluating the detection performance of the proposed system.

IV. Results and Discussion

The results of the experiments clearly demonstrate the effectiveness of in-situ vibration and acoustic data fusion for defect detection in additive manufacturing. The fused system achieved an average F1-score of 92.4%, significantly outperforming vibration-only (81.7%) and acoustic-only (85.3%) systems. The ROC curve for the fused model showed an area under the curve (AUC) of 0.96, compared to 0.84 and 0.88 for vibration and acoustic systems respectively. These results indicate that data fusion enhances both sensitivity (true positive rate) and specificity (true negative rate) of defect detection [11].

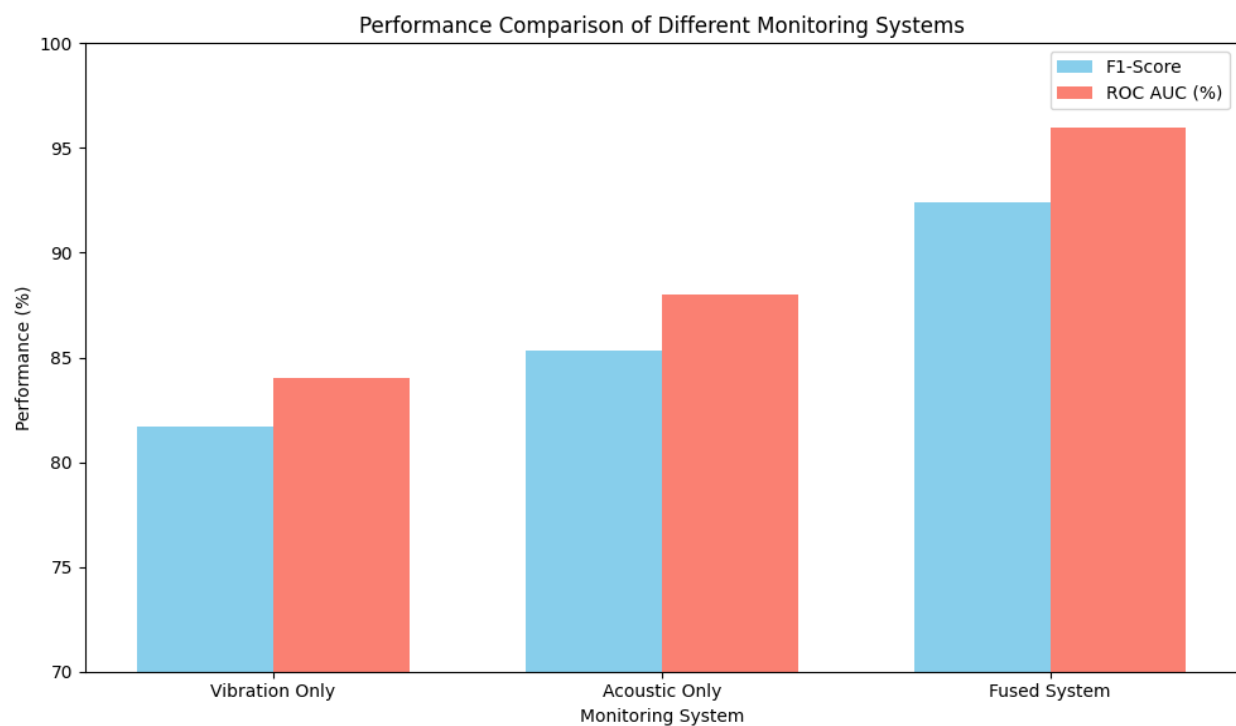


Figure 1: illustrates a comparison of F1-scores and ROC AUCs for vibration-only, acoustic-only, and fused data systems

A detailed breakdown of defect types revealed that the fusion approach was particularly effective in detecting lack of fusion defects, where the individual sensors showed limitations. Vibration sensors often missed subtle defects that did not induce significant mechanical disturbances, while acoustic sensors occasionally failed to capture defects masked by background noise. Combining both modalities mitigated these weaknesses, providing a comprehensive detection capability that could identify a wider range of anomalies with higher reliability. The early detection capability was another notable advantage [12]. In several instances, defects were detected up to 20 seconds

earlier in the fused system compared to single-sensor systems. Early detection is critical for real-time intervention, enabling corrective measures such as modifying process parameters or halting the build to prevent further defects. This capability underscores the practical value of the proposed monitoring system for industrial adoption.

False positive rates were also significantly reduced through multi-modal fusion. In single-sensor systems, transient disturbances from environmental noise or machine operations occasionally triggered false alarms. By requiring corroborative evidence from both vibration and acoustic signals, the fused system could distinguish genuine defects from spurious events, enhancing overall system reliability and operator trust. Importantly, the data fusion approach demonstrated robustness across different build geometries and process conditions. Tests on parts with varying complexity, from simple cubes to intricate lattice structures, showed consistent defect detection performance [13]. This robustness indicates that the proposed method is not highly sensitive to minor variations in the manufacturing environment, making it a strong candidate for widespread deployment across diverse AM platforms and applications.

V. Conclusion

This study presents a novel and highly effective method for enhanced defect detection in additive manufacturing through the fusion of in-situ vibration and acoustic emission data. By leveraging the complementary strengths of these two sensing modalities and employing advanced signal processing and machine learning techniques, we demonstrate significant improvements in defect detection sensitivity, specificity, and early warning capabilities. The experimental results clearly validate the superior performance of the fused system over single-modality approaches, highlighting its robustness, reliability, and practical applicability across diverse manufacturing scenarios. Our findings strongly advocate for the adoption of multi-modal in-situ monitoring as a standard practice in the AM industry to ensure higher quality, reduced waste, and enhanced component reliability. Future work will focus on extending this approach to other AM technologies, integrating additional sensing modalities, and implementing real-time adaptive feedback mechanisms for automated process control.

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